

AHRQ Quality Indicators Risk Adjustment and Hierarchical Modeling Approaches

1 Introduction

The Inpatient Quality Indicators (IQIs) are a set of measures that provide a perspective on hospital quality of care using hospital administrative data. These indicators reflect quality of care inside hospitals and include inpatient mortality for certain procedures and medical conditions; utilization of procedures for which there are questions of overuse, underuse, and misuse; and volume of procedures for which there is some evidence that a higher volume of procedures is associated with lower mortality.

The IQIs are a software tool distributed free by the Agency for Healthcare Research and Quality (AHRQ). The software can be used to help hospitals identify potential problem areas that might need further study and which can provide an indirect measure of in-hospital quality of care. The IQI software programs can be applied to any hospital inpatient administrative data. These data are readily available and relatively inexpensive to use.

Inpatient Quality Indicators:

- Can be used to help hospitals identify potential problem areas that might need further study.
- Provide the opportunity to assess quality of care inside the hospital using administrative data found in the typical discharge record.
- Include 15 mortality indicators for conditions or procedures for which mortality can vary from hospital to hospital.
- Include 11 utilization indicators for procedures for which utilization varies across hospitals or geographic areas.
- Include 6 volume indicators for procedures for which outcomes may be related to the volume of those procedures performed.
- Are publicly available without cost, and are available for download

The IQIs include the following 32 measures:

1. Mortality Rates for Medical Conditions (7 Indicators)
 - Acute myocardial infarction (AMI) (IQI 15)
 - AMI, Without Transfer Cases (IQI 32)
 - Congestive heart failure (IQI 16)
 - Stroke (IQI 17)
 - Gastrointestinal hemorrhage (IQI 18)
 - Hip fracture (IQI 19)
 - Pneumonia (IQI 20)
2. Mortality Rates for Surgical Procedures (8 Indicators)

- Esophageal resection (IQI 8)
 - Pancreatic resection (IQI 9)
 - Abdominal aortic aneurysm repair (IQI 11)
 - Coronary artery bypass graft (IQI 12)
 - Percutaneous transluminal coronary angioplasty (IQI 30)
 - Carotid endarterectomy (IQI 31)
 - Craniotomy (IQI 13)
 - Hip replacement (IQI 14)
3. Hospital-level Procedure Utilization Rates (7 Indicators)
- Cesarean section delivery (IQI 21)
 - Primary Cesarean delivery (IQI 33)
 - Vaginal Birth After Cesarean (VBAC), Uncomplicated (IQI 22)
 - VBAC, All (IQI 34)
 - Laparoscopic cholecystectomy (IQI 23)
 - Incidental appendectomy in the elderly (IQI 24)
 - Bi-lateral cardiac catheterization (IQI 25)
4. Area-level Utilization Rates (4 Indicators)
- Coronary artery bypass graft (IQI 26)
 - Percutaneous transluminal coronary angioplasty (IQI 27)
 - Hysterectomy (IQI 28)
 - Laminectomy or spinal fusion (IQI 29)
5. Volume of Procedures (6 Indicators)
- Esophageal resection (IQI 1)
 - Pancreatic resection (IQI 2)
 - Abdominal aortic aneurysm repair (IQI 4)
 - Coronary artery bypass graft (IQI 5)
 - Percutaneous transluminal coronary angioplasty (IQI 6)
 - Carotid endarterectomy (IQI 7)

2 Statistical Methods

This section provides a brief overview of the structure of the administrative data from the Nationwide Inpatient Sample, and the statistical models and tools currently being used within the AHRQ Quality Indicators Project. We then propose several alternative statistical models and methods for consideration, including (1) models that account for trends in the response variable over time; and (2) statistical approaches that adjust for the potential positive correlation on patient outcomes from the same provider. We provide an overview of how these proposed alternative statistical approaches will impact the fitting of risk-adjusted models to the reference population, and on the tools that are provided to users of the QI methodology.

This is followed by an overview of the statistical modeling investigation, including (1) the selection of five IQIs to investigate in this report, (2) fitting current and alternative statistical models to data from the Nationwide Inpatient Sample, (3) statistical methods to compare parameter estimates between current and alternative modeling approaches using a Wald test-statistic, and (4) statistical methods to compare differences between current and alternative modeling approaches on provider-level model predictions (expected and risk-adjusted rates).

2.1 *Structure of the Administrative Data*

Hospital administrative data are collected as a routine step in the delivery of hospital services throughout the U.S., and provide information on diagnoses, procedures, age, gender, admission source, and discharge status on all admitted patients. These data can be used to describe the quality of medical care within individual providers (hospitals), within groups of providers (e.g., states, regions), and across the nation as a whole. Although in certain circumstances quality assessments based on administrative data are potentially prone to bias compared to possibly more clinically detailed data sources such as medical chart records, the fact that administrative data are universally available among the 37 States participating in the Healthcare Cost and Utilization Project (HCUP) allowed AHRQ to develop analytical methodologies to identify potential quality problems and success stories that merit further investigation and study.

The investigation in this report focuses on five select inpatient quality indicators, as applied to the Nationwide Inpatient Sample (NIS) from 2001-2003. The Nationwide Inpatient Sample represents a sample of administrative records from a sample of approximately 20 percent of the providers participating in the HCUP. There is significant overlap in the HCUP hospitals selected in the NIS, with several of the hospitals being repeatedly sampled in more than one year.

The NIS data is collected at the patient admission level. For each hospital admission, data is collected on patient age, gender, admission source, diagnoses, procedures, and discharge status. There is no unique patient identifier, so the same patient may be

represented more than once in the NIS data (with some patients potentially being represented more than once within the same hospital, and other patients potentially being represented more than once within multiple hospitals).

The purpose of the QI statistical models is to provide parameter estimates for each quality indicator that are adjusted for age, gender, and all patient refined diagnosis related group (APR-DRG). The APR-DRG classification methodology was developed by 3M, and provides a basis to adjust the QIs for the severity of illness or risk of mortality, and is explained elsewhere.

For each selected quality indicator, the administrative data is coded to indicate whether they contain the outcome of interest as follows:

Let Y_{ijk} represent the outcome for the j^{th} patient admission within the i^{th} hospital, for the k^{th} Quality Indicator. Y_{ijk} is equal to one for patients who experience the adverse event, zero for patients captured within the appropriate reference population but do not experience the adverse event, and is missing for all patients that are excluded from the reference population for the k^{th} Quality Indicator.

For each Quality Indicator, patients with a missing value for Y_{ijk} are excluded from the analysis dataset. For all patients with $Y_{ijk} = 0$ or 1, appropriate age-by-gender and APR-DRG explanatory variables are constructed for use in the statistical models.

2.2 Current Statistical Models and Tools

The following two subsections provide a brief overview of the statistical models that are currently fit to the HCUP reference population, and the manner in which these models are utilized in software tools provided by the AHRQ Quality Indicators Project.

2.2.1 Models for the Reference Population

Currently, a simple logistic regression model is applied to three years of administrative data from the HCUP for each Quality Indicator, as follows:

$$\log it(Pr(Y_{ijk} = 1)) = \beta_{k0} + \sum_{p=1}^{P_k} \alpha_{kp} \cdot (Age / Gender_p)_{ij} + \sum_{q=1}^{Q_k} \theta_{kq} \cdot (APR - DRG_q)_{ijk}, \quad (1)$$

where Y_{ijk} represents the response variable for the j^{th} patient in the i^{th} hospital for the k^{th} quality indicator; $(Age/Gender_p)_{ij}$ represents the p^{th} age-by-gender zero/one indicator variable associated with the j^{th} patient in the i^{th} hospital; and $(APR-DRG_q)_{ijk}$ represents the q^{th} APR-DRG zero/one indicator variable associated with the j^{th} patient in the i^{th} hospital for the k^{th} quality indicator.

For the k^{th} quality indicator, we assume that there are P_k age-by-gender categories and Q_k APR-DRG categories that will enter the model for risk-adjustment purposes.

The α_{kp} parameters capture the effects of each of the P_k age-by-gender categories on the QI response variable; and similarly, the θ_{kq} parameters capture the effects of each of the

Q_k APR-DRG categories on the QI response variable. The α_{kp} and θ_{kq} parameters each have ln(odds-ratio) interpretation, when compared to the reference population. The logit-risk of an adverse outcome for the reference population is captured by the β_{k0} intercept term in the model associated with the k^{th} Quality Indicator.

Model (1) can be fit using several procedures in SAS. For simplicity and consistency with other modeling approaches investigated in this report, we used SAS Proc Genmod to fit Model (1) to data from the Nationwide Inpatient Sample.

2.2.2 Software Tools Provided to Users

The AHRQ Quality Indicators Project provides access to software that can be downloaded by users to calculate expected and risk-adjusted QIs for their own sample of administrative data. The expected rate represents the rate that the provider would have experienced if it's quality of performance was identical to the reference (National) population, given the provider's actual case mix (e.g. age, gender, DRG and comorbidity categories). Expected rates are calculated based on combining the regression coefficients from the reference model (based on fitting Model (1) above to the reference HCUP population) with the patient characteristics from a specific provider.

Risk-adjusted rates are the estimated performance if the provider had an "average" patient mix, given their actual performance. It is the most appropriate rate upon which to compare *across hospitals*, and is calculated by adjusting the observed National Average Rate for the ratio of observed vs. expected rates at the provider-level:

$$\text{Risk-adjusted rate} = (\text{Observed Rate} / \text{Expected Rate}) \times \text{National Average Rate} \quad (2)$$

The AHRQ Inpatient Quality Indicator software appropriately applies the National Model Regression Coefficients to the provider specific administrative records being analyzed to calculate both expected and risk-adjusted rates.

2.3 Alternative Statistical Methods

In the following sections, we propose several alternative statistical models and methods for consideration, including (1) models that account for trends in the response variable over time; and (2) statistical approaches that adjust for the potential positive correlation on patient outcomes from the same provider.

2.3.1 Adjusting for Trends over Time

The following alternative model formulation is proposed as a simple method for adjusting for the effects of quality improvement over time with the addition of a single covariate to Model (1):

$$\log \text{it}(\text{Pr}(Y_{ijk} = 1)) = \beta_{k0} + \sum_{p=1}^{P_k} \alpha_{kp} \cdot (\text{Age} / \text{Gender}_p)_{ij} + \sum_{q=1}^{Q_k} \theta_{kq} \cdot (\text{APR} - \text{DRG}_q)_{ijk} + \lambda_k \cdot (\text{Year}_{ijk} - 2002) \quad (3)$$

The parameter λ_k adjusts the model for a simple linear trend over time (on the logit-scale for risk of an adverse event), with the covariate ($\text{Year}_{ijk}-2002$) being a continuous variable that captures the calendar year that the j^{th} patient was admitted to the i^{th} hospital. This time-trend covariate is centered on calendar year 2002 in our analyses, to preserve a similar interpretation of the β_{k0} intercept term in Model (1), as our national reference dataset represents administrative records reported in calendar years 2001 through 2003.

Additional complexities can be introduced into the above simple time-trend model to investigate (1) non-linear time-trends on the logit scale, and (2) any changes over time in the age-by-gender or APR-DRG variable effects on risk of adverse outcomes. Such investigations were not explored within this report – but could be the subject of later data analyses. The authors of this report also suggest combining data over a longer period of time (e.g., five years or more) to better capture long-term trends in hospital quality of care.

The introduction of a time-trend into the model serves three purposes. First, it provides AHRQ (and users) with an understanding of how hospital quality is changing over time through the interpretation of the λ_k parameter (or similar time-trend parameters in any expanded time-trend model). Secondly, if the λ_k parameter is found to be statistically significant, the time-trend model will likely offer more precise expected and risk-adjusted rates. Thirdly, it may allow more accurate model predictions (expected and risk-adjusted rates for providers) when users apply a model based on older data to more recent data (often, a user might utilize software that is based on a 2001-2003 reference population to calculate rates for provider-specific data from calendar year 2005).

2.3.2 Adjusting for Within-Provider Correlation

The current simple logistic regression modeling approach being used by AHRQ in the risk-adjusted model fitting assumes that all patient responses are independent and identically distributed. However, it is likely that responses of patients from within the same hospital may be correlated, even after adjusting for the effects of age, gender, severity of illness and risk of mortality. This anticipated positive correlation results from the fact that each hospital has a unique mixture of staff, policies and medical culture that combine to influence patient results. It is often the case that fitting simple models to correlated data results in similar parameter estimates, but biased standard errors of those parameter estimates – however, this does not always hold true. In the following two subsections, we provide an overview of generalized estimating equations (GEE) and generalized linear mixed modeling (GLMMIX) approaches for adjusting the QI statistical models for the anticipated effects of within-provider correlation. These approaches will be investigated on a sample of five selected Quality Indicators to determine whether (or not) the parameter estimates from a simple logistic regression model result in different parameter estimates or provider-level model predictions (expected and risk adjusted rates), in comparison to GEE or GLMMIX approaches that account for the within-provider correlation.

2.3.2.1 Generalized Estimating Equations

In many studies, we are faced with a problem where the responses Y_i are not independent of each other ($\text{Cov}[Y_i, Y_j] \neq 0$ when $i \neq j$). The responses from studies with correlated data can often be organized into clusters, where observations from within a cluster are dependent, and observations from two different clusters are independent:

Y_{ij} is the j^{th} response from the i^{th} cluster: $\text{Cov}[Y_{ij}, Y_{i'j'}] = 0$ when $i \neq i'$
 $\text{Cov}[Y_{ij}, Y_{ij'}] \neq 0$ when $j \neq j'$

In the context of the AHRQ Quality Indicators project, the providers (hospitals) serve as clusters. There are usually two objectives for the analysis of clustered data:

- 1) Describing the response variable Y_{ij} as a function of explanatory variables (X_{ij}), and
- 2) Measuring the within-cluster dependence.

When Y_{ij} is continuous and follows a normal distribution, there is a well developed set of statistical methodology for meeting the above two objectives. This methodology usually assumes that the residuals from within each cluster are jointly normal, so that each cluster is distributed $\text{MVN}(X_i\beta, \Sigma_i)$. Thus, when faced with normally distributed dependent responses, the assumption of a multivariate normal distribution allows us to model clustered data with our usual maximum likelihood solutions.

When the response variable does not follow a normal distribution, we are often left without a multivariate generalization which allows us to meet the two objectives for the analysis of clustered data through use of a maximum likelihood solution. For example, there are no multivariate extensions of the binomial distribution that provides a likelihood function for clustered data.

The theory of Generalized Estimating Equations (GEE) provides a statistical methodology for analyzing clustered data under the conceptual framework of Generalized Linear Models. GEE was developed in 1986 by Kung-Yee Liang and Scott Zeger, and is an estimating procedure which makes use of Quasi-Likelihood theory under a marginal model.

When the regression analysis for the mean is of primary interest, the β coefficients can be estimated by solving the following estimating equation:

$$U_1(\beta, \alpha) = \sum_{i=1}^K \left(\frac{\partial \mu_i}{\partial \beta} \right)' \text{cov}^{-1}(Y_i; \beta, \alpha) (Y_i - \mu_i(\beta)) = 0$$

where $\mu_i(\beta) = E[Y_i]$, the marginal expectation of Y_i

Note that U_1 (the GEE) has exactly the same form as the score equation from a simple logistic regression model, with the exception that:

- 1) Y_i is now an $n_i \times 1$ vector which comprises the n_i observations from the i^{th} cluster
- 2) The covariance matrix, $\text{cov}(Y_i)$, for Y_i depends not only on β , but on α which characterizes the within cluster dependence.

The additional complication of the parameter α can be alleviated by iterating until convergence between solving $U_1(\beta, \alpha(\beta)) = 0$ and updating $\alpha(\beta)$, an estimate of α . Thus, the GEE approach is simply to choose parameter values β so that the expected $\mu_i(\beta)$ is as close to the observed Y_i as possible, weighting each cluster of data inversely to its variance matrix $\text{cov}(Y_i; \beta, \alpha)$ which is a function of the within-cluster dependence.

The marginal GEE approach has some theoretical and practical advantages:

- 1) No joint distribution assumption for $Y_i = (Y_{i1}, \dots, Y_{ini})$ is required to use the method. The GEE approach utilizes a method of moments estimator for α , the within-cluster dependence parameter.
- 2) β , the solution of $U_1(\beta, \alpha(\beta)) = 0$, has high efficiency compared to the maximum likelihood estimate of β in many cases studied.
- 3) Liang and Zeger have proposed the use of both a model-based and a robust variance of β . The model-based variance of β is more efficient – but is sensitive to misspecification of the model for within-cluster dependence. The robust variance is less efficient, but provides valid inferences for β even when the model for dependence is misspecified.

Specifically, suppose the investigators mistakenly assume that the observations from the same cluster are independent from each other. The 95% confidence interval for each regression coefficient β_j , $j=1, \dots, p$, based upon $\beta_j \pm 1.96 (V_\beta)^{1/2}$ remains valid in large sample situations. Thus, investigators are protected against misspecification of the within-cluster dependence structure. This is especially appealing when the data set is comprised of a large number of small clusters.

When the within-cluster dependence is of primary interest, this marginal GEE approach has an important limitation – in that β and α are estimated as if they are independent of each other. Consequently, very little information from β is used when estimating α .

The marginal model for correlated binary outcomes (such as those from the AHRQ QI Project) can be thought of as a simple extension to a simple logistic regression model that directly incorporates the within-cluster correlation among patient responses from within the same hospital. To estimate the regression parameters in a marginal model, we make assumptions about the marginal distribution of the response variable (e.g. assumptions about the mean, its dependence on the explanatory variables, the variance of each Y_{ij} , and the covariance among responses from within the same hospital). The cross-sectional model (Model (1)) and time-trend model (Model (3)) can be fit using the generalized

estimating equations approach using SAS Proc Genmod, through the introduction of a repeated statement that accounts for the within-provider clustering.

2.3.2.2 Generalized Linear Mixed Models

In the previous section, we described marginal models for correlated/clustering data using a generalized estimating equations approach. An alternative approach for accounting for the within-hospital correlation is through the introduction of random effects into Model(1) as follows:

$$\log it(Pr(Y_{ijk} = 1)) = \beta_{k0} + \sum_{p=1}^{P_k} \alpha_{kp} \cdot (Age / Gender_p)_{ij} + \sum_{q=1}^{Q_k} \theta_{kq} \cdot (APR - DRG_q)_{ijk} + \gamma_{ki}, \quad (4)$$

where γ_{ki} is a random effect associated with each provider, and is assumed to follow a normal distribution with mean zero, and variance σ_{Hosp}^2 . The time-trend model can be similarly expanded using a random effects model, as follows:

$$\log it(Pr(Y_{ijk} = 1)) = \beta_{k0} + \sum_{p=1}^{P_k} \alpha_{kp} \cdot (Age / Gender_p)_{ij} + \sum_{q=1}^{Q_k} \theta_{kq} \cdot (APR - DRG_q)_{ijk} + \lambda_k \cdot (Year_{ijk} - 2002) + \gamma_{0ki} + \gamma_{1ki} \cdot (Year_{ijk} - 2002), \quad (5)$$

where γ_{0ki} and γ_{1ki} are random intercept and slope terms associated with each provider (thus allowing each provider to depart from the fixed effects portion of the model with a provider-specific trend over time). In Model (5), we assume that γ_{0ki} and γ_{1ki} jointly follow a multivariate normal distribution with mean zero and covariance matrix

$$\Sigma = \begin{bmatrix} \sigma_{Hosp}^2 & \sigma_{Hosp / Year}^2 \\ \sigma_{Hosp / Year}^2 & \sigma_{Year}^2 \end{bmatrix}.$$

Models (4) and (5) can be fit using SAS Proc GLIMMIX, and can also be expanded to allow for different probability distributions for the random effects (i.e. we can relax the assumption of normality for the random effects, if necessary).

2.3.3 Impact of Adopting Alternative Methods on Model Fitting and Tools

Currently, the risk-adjusted models for each quality indicator are fit to three calendar years of administrative data from the HCUP using various different data manipulations and model fitting procedures available from within the SAS software system. The addition of a time-trend covariate (or series of covariates) will not introduce any significant additional complexity to fitting these models to the reference (national) data. Adjusting the models for the anticipated positive correlation among patient responses from within the same hospital will require the use of Generalized Estimating Equations (GEE) approaches available through Proc GENMOD in SAS, or the use of Generalized Linear Mixed Modeling (GLMMIX) approaches available through Proc GLIMMIX in

SAS. Both of these methods are more computationally intense compared to fitting a simple logistic regression model, and may be subject to convergence problems and model mis-specification that is typical of such iterative modeling approaches.

Once the models are fit to the reference (national) population, integration of the modeling results into the software tools provided to users should be relatively straightforward. The introduction of a time-trend model would require the user to keep track of the calendar year associated with each patient response, for inclusion as a predictor variable in the model. If additional time-trend variables (either non-linear, or interactions with the other predictor variables) are introduced, the software can be quickly updated to accommodate these model changes.

Use of the GLMMIX approach may yield additional information, in which the vector of random effects from the National Model can be exploited to determine the distribution of expected risk of adverse events (after adjusting for age, gender, severity of illness, and risk of mortality) across participating hospitals. This distribution can be used to identify (approximately) where within the national distribution of providers a particular hospital lies (currently, the AHRQ methodology only provides information related to whether an individual user is above or below the national mean). This use of the estimated vector of random effects would require additional software development at AHRQ, as well as additional work to ensure that the GLMMIX random effects model is adequately fitting the data from the reference population.

2.4 Overview of Statistical Modeling Investigation

The purpose of this report is to investigate the use of alternative modeling approaches to potentially adjust the risk-adjusted Quality Indicator Models for the effects of trends over time and the effects of positive correlation among responses from within the same hospital. In the following sections, we provide:

- an overview of the five Inpatient Quality Indicators that were selected for this investigation;
- a description of the various models fit to the Nationwide Inpatient Sample;
- statistical methodology used to assess whether or not the alternative modeling approaches yield parameter estimates that are significantly different from each other; and
- statistical methodology used to assess whether or not the alternative modeling approaches yield provider-level estimates (expected and risk-adjusted rates of adverse events) that are significantly different from each other.

2.4.1 Selection of IQIs to Investigate

The following five Inpatient Quality Indicators were selected for exploration in this report (*with the descriptions for each QI copied directly from the AHRQ Guide to Prevention Quality Indicators*):

IQI 11: Abdominal Aortic Aneurysm Repair Mortality Rate

Abdominal aortic aneurysm (AAA) repair is a relatively rare procedure that requires proficiency with the use of complex equipment; and technical errors may lead to clinically significant complications, such as arrhythmias, acute myocardial infarction, colonic ischemia, and death. The adverse event for this Quality Indicator is recorded as positive for any patient who dies with a code of AAA repair in any procedure field, and a diagnosis of AAA in any field. The reference population for this Quality Indicator includes any patient discharge with ICD-9-CM codes of 3834, 3844, and 3864 in any procedure field and a diagnosis code of AAA in any field. The reference population excludes patients with missing discharge disposition, who transfer to another short-term hospital, MDC 14 (pregnancy, childbirth, and puerperium), and MDC 15 (newborns and other neonates).

IQI 14: Hip Replacement Mortality Rate

Total hip arthroplasty (without hip fracture) is an elective procedure preformed to improve function and relieve pain among patients with chronic osteoarthritis, rheumatoid arthritis, or other degenerative processes involving the hip joint. The adverse event for this Quality Indicator is recorded as positive for any patient who dies with a code of partial or full hip replacement in any procedure field. The reference population for this Quality Indicator includes any patient with procedure code of partial or full hip replacement in any field, and includes only discharges with uncomplicated cases: diagnosis codes for osteoarthritis of hip in any field. The reference population excludes patients with missing discharge disposition, who transfer to another short-term hospital, MDC 14 (pregnancy, childbirth, and puerperium), and MDC 15 (newborns and other neonates).

IQI 17: Acute Stroke Mortality Rate

Quality treatment for acute stroke must be timely and efficient to prevent potentially fatal brain tissue death, and patients may not present until after the fragile window of time has passed. The adverse event for this Quality Indicator is recorded as positive for any patient who dies with a principal diagnosis code of stroke. The reference population for this Quality Indicator includes any patient aged 18 or older with a principal diagnosis code of stroke. The reference population excludes patients with missing discharge disposition, who transfer to another short-term hospital, MDC 14 (pregnancy, childbirth, and puerperium), and MDC 15 (newborns and other neonates).

IQI 19: Hip Fracture Mortality Rate

Hip fractures, which are a common cause of morbidity and functional decline among elderly patients are associated with a significant increase in the subsequent risk of mortality. The adverse event for this Quality Indicator is recorded as positive for any

patient who dies with a principal diagnosis code of hip fracture. The reference population for this Quality Indicator includes any patient aged 18 or older with a principal diagnosis code of hip fracture. The reference population excludes patients with missing discharge disposition, who transfer to another short-term hospital, MDC 14 (pregnancy, childbirth, and puerperium), and MDC 15 (newborns and other neonates).

IQI 25: Bilateral Cardiac Catheterization Rate

Right-side coronary catheterization incidental to left side catheterization has little additional benefit for patient without clinical indications for right-side catheterization. The adverse event for this Quality Indicator is recorded as positive for any patient with coronary artery disease who has simultaneous right and left heart catheterizations in any procedure field (excluding valid indications for right-sided catheterization in any diagnosis field, MDC 14 (pregnancy, childbirth, and puerperium), and MDC 15 (newborns and other neonates)). The reference population for this Quality Indicator includes any patient with coronary artery disease discharged with heart catheterization in any procedure field. The reference population excludes patients with MDC 14 (pregnancy, childbirth, and puerperium), and MDC 15 (newborns and other neonates).

2.4.2 Fitting Current and Alternative Models to NIS Data

For each selected IQI, we fit risk-adjusted cross-sectional and time-trend adjusted models using a simple logistic regression, generalized estimating equations and generalized linear mixed modeling approach (for a combined six models for each IQI). The models were fit to three-years of combined data from the Nationwide Inpatient Sample, which represents an approximate 20 percent sample of hospitals from within the HCUP (with administrative records included for all patients treated within each selected hospital).

The data were processed to eliminate any patient records that are excluded from the reference population prior to modeling (thus, only patients with a zero or one response were included in the analysis for each IQI). The form of the model followed what was included in the models currently fit to the HCUP data – with minor modifications to remove covariates that represented very sparse cells.

For the GEE and GLMMIX approaches, we retained both the robust and model-based variance/covariance matrices for the vector of parameter estimates, to allow for appropriate statistical comparisons using both methods. We also retained the vector of random effects from the GLMMIX approach, to assess for distributional assumptions.

2.4.3 Methods to Compare Parameter Estimates

Given that the parameter estimates from each of the logistic regression models follow an approximate normal distribution (as shown in McCulloch & Nelder, 1989 within the Generalized Linear Model conceptual framework), a Wald Statistic can be used to assess whether there are statistically significant differences between a specific pair of modeling approaches. For example, when comparing the simple linear regression model results to the results of the GEE approach, we have the following three potential Wald Statistics:

$$\begin{aligned} W_1 &= (\hat{\beta}_{SLR} - \hat{\beta}_{GEE})^T V_{\beta_{SLR}}^{-1} (\hat{\beta}_{SLR} - \hat{\beta}_{GEE}) \\ W_2 &= (\hat{\beta}_{SLR} - \hat{\beta}_{GEE})^T V_{\beta_{GEE-Model}}^{-1} (\hat{\beta}_{SLR} - \hat{\beta}_{GEE}) \\ W_3 &= (\hat{\beta}_{SLR} - \hat{\beta}_{GEE})^T V_{\beta_{GEE-Robust}}^{-1} (\hat{\beta}_{SLR} - \hat{\beta}_{GEE}) \end{aligned}$$

In the above formulas, $\hat{\beta}_{SLR}$ and $\hat{\beta}_{GEE}$ represent the parameter estimates from the simple logistic and GEE models. $V_{\beta_{SLR}}^{-1}$ represents the inverse of the variance-covariance matrix of the regression parameters from the simple logistic regression model. Similarly, $V_{\beta_{GEE-Model}}^{-1}$ and $V_{\beta_{GEE-Robust}}^{-1}$ represent the inverse of the model-based and robust variance-covariance matrix of the regression parameters from the GEE regression model.

Under the null hypothesis, that there are no statistically significant differences between the simple logistic regression model and GEE parameter estimates, the above three Wald test statistics are expected to follow a $X^2_{(p)}$ distribution (a Chi-squared distribution with p degrees of freedom, where p represents the number of explanatory variables that were used within the statistical model).

2.4.4 Methods to Compare Provider-Level Model Predictions

For each select IQI, we identified a simple random sample of 50 providers to use for assessing differences between provider-level model predictions (both expected and risk-adjusted rates). Simple descriptive statistics (mean and standard deviation) were generated for the distribution differences in provider-level model predictions to assess whether (or not) changes in the model might result in any potential bias or increased variability in provider-level estimates.

The distributional summaries were conducted separately for the cross-sectional and time-trend models (so that the statistics isolate any differences attributable to adjusting the models for the potential correlation among responses within the same provider).

Subsequent analyses will be conducted at a later date to provide comparisons between the cross-sectional and time-trend models within each model type (and potentially across model types).

3 Results

All models were successfully fit to the NIS data source. The GLMMIX approach initially suffered from convergence problems while using the default optimization techniques, but converged for all five IQIs (both cross sectional and time-trend adjusted models) when using Newton-Raphson optimization with ridging. Due to the large sample size of the dataset, the personal computer used to fit the model ran out of memory when calculating the robust variance-covariance matrix associated with the parameter estimates for IQI-25 with the GLMMIX approach (the computer had 2GB of RAM).

Section 3.1 below provides summary statistics for the quality indicator response variables that were modeled from within the National Inpatient Sample. Sections 3.2 through 3.6 provide model results for each of the five select IQIs explored in this report.

3.1 Summary Statistics for NIS Data

Table 3.1 below provides summary statistics for the five selected quality indicators. The summary statistics include:

- The number of adverse events observed
- The number of patients in the reference population
- The number of hospitals that had patients within the reference population
- The mean response (proportion of patients who experienced the adverse event)
- The standard error associated with the mean response
- Select percentiles from the distribution (5th, 25th, 50th, 75th, and 95th)

Separate summary statistics were generated for each year of data (2001, 2002, and 2003) and then for all years combined. Prior to calculating the mean, standard error, and percentiles, the responses were averaged at the hospital level. These statistics therefore represent the distribution of hospital mean responses, and are presented in two ways (weighted and unweighted). The weighted results weigh each provider according to the number of patients observed within the reference population, whereas the unweighted results treat each hospital equally.

The weighted analysis mean was used as the National Average Rate when constructing the provider-specific risk-adjusted rates. Conceptually, the standard-error of the mean from the unweighted analysis should be proportional to the standard-error of the mean from the vector of random effects intercepts generated using the GLMMIX approach from the cross-sectional model (although we anticipate that the variability of the random effects would be smaller due to the fact that other factors (age, gender, severity of illness and risk of mortality) are explaining variability in the Quality Indicator response variable).

Table 3.1 Summary Statistics (at the Provider Level) for the Five Selected Quality Indicators

IQI	Year	Analysis Type	Summary Statistics									
			n _{cases}	n _{Pop}	n _{Hosp}	Mean	Std Error	5 th %ile	25 th %ile	50 th %ile	75 th %ile	95 th %ile
11	2001	Unweighted	726	8833.0	470	0.141	0.010	0.000	0.000	0.067	0.161	0.500
		Weighted				0.082	0.004	0.000	0.032	0.063	0.107	0.222
	2002	Unweighted	655	8099.0	449	0.152	0.011	0.000	0.000	0.070	0.188	0.750
		Weighted				0.081	0.005	0.000	0.028	0.063	0.098	0.231
	2003	Unweighted	558	8144.0	447	0.132	0.011	0.000	0.000	0.050	0.143	0.500
		Weighted				0.069	0.004	0.000	0.027	0.048	0.078	0.200
	All Years	Unweighted	1939	25076	1050	0.149	0.007	0.000	0.000	0.071	0.176	0.667
		Weighted				0.077	0.003	0.000	0.034	0.057	0.094	0.208
14	2001	Unweighted	104	34628	687	0.004	0.001	0.000	0.000	0.000	0.000	0.022
		Weighted				0.003	0.000	0.000	0.000	0.000	0.001	0.015
	2002	Unweighted	112	39677	682	0.004	0.001	0.000	0.000	0.000	0.000	0.020
		Weighted				0.003	0.000	0.000	0.000	0.000	0.002	0.014
	2003	Unweighted	86	39068	689	0.004	0.001	0.000	0.000	0.000	0.000	0.016
		Weighted				0.002	0.000	0.000	0.000	0.000	0.000	0.012
	All Years	Unweighted	302	113373	1544	0.004	0.000	0.000	0.000	0.000	0.000	0.020
		Weighted				0.003	0.000	0.000	0.000	0.000	0.003	0.013
17	2001	Unweighted	12616	108886	957	0.115	0.003	0.000	0.065	0.105	0.143	0.250
		Weighted				0.116	0.002	0.045	0.086	0.115	0.140	0.186
	2002	Unweighted	12298	109670	959	0.113	0.003	0.000	0.067	0.103	0.143	0.250
		Weighted				0.112	0.001	0.050	0.084	0.112	0.134	0.183
	2003	Unweighted	12385	108720	951	0.108	0.003	0.000	0.060	0.100	0.139	0.238
		Weighted				0.114	0.001	0.046	0.087	0.112	0.137	0.194
	All Years	Unweighted	37299	327276	2095	0.111	0.002	0.000	0.069	0.102	0.141	0.238
		Weighted				0.114	0.001	0.053	0.089	0.112	0.136	0.184
19	2001	Unweighted	1916	60318	809	0.036	0.003	0.000	0.000	0.026	0.044	0.095
		Weighted				0.032	0.001	0.000	0.017	0.031	0.043	0.066
	2002	Unweighted	2008	60597	800	0.039	0.003	0.000	0.000	0.026	0.047	0.092
		Weighted				0.033	0.001	0.000	0.019	0.031	0.044	0.069
	2003	Unweighted	1919	60559	804	0.037	0.003	0.000	0.000	0.024	0.043	0.100
		Weighted				0.032	0.001	0.000	0.019	0.029	0.040	0.070
	All Years	Unweighted	5843	181474	1806	0.038	0.002	0.000	0.000	0.027	0.044	0.091
		Weighted				0.032	0.000	0.005	0.020	0.031	0.041	0.065
25	2001	Unweighted	22858	283099	437	0.098	0.006	0.000	0.032	0.065	0.121	0.293
		Weighted				0.081	0.003	0.018	0.037	0.061	0.103	0.208
	2002	Unweighted	21455	286259	444	0.085	0.005	0.000	0.030	0.057	0.111	0.255
		Weighted				0.075	0.003	0.014	0.038	0.059	0.097	0.196
	2003	Unweighted	21697	298744	455	0.086	0.005	0.000	0.026	0.056	0.103	0.267
		Weighted				0.073	0.003	0.015	0.031	0.056	0.087	0.201
	All Years	Unweighted	66010	868102	997	0.090	0.004	0.000	0.029	0.057	0.107	0.261
		Weighted				0.076	0.002	0.017	0.037	0.057	0.095	0.208

3.2 IQI 11 – Abdominal Aortic Aneurysm Repair Mortality Rate

3.2.1 Model Parameter Estimates

Below we provide the model parameter estimates from fitting the simple logistic regression, generalized estimating equations, and generalized linear mixed model to the 2001-2003 Nationwide Inpatient Sample for IQI 11 (Abdominal Aortic Aneurysm Repair Mortality Rate). Table 3.2.1a provides the parameter estimates associated with the cross-sectional model, and Table 3.2.1b provides the parameter estimates associated with the model that adjusts for a simple linear trend over time. Across these two tables, we see that the parameter estimates and associated standard errors are quite comparable among the three modeling approaches. In fact, the estimated correlation coefficient from the GEE modeling approach is nearly zero in both the cross-sectional ($\rho=0.0073$) and time-trend adjusted ($\rho=0.0073$) models. The estimated variance components associated with provider-specific random effects from the GLIMMIX model were subtle, yet statistically significant in both models ($\sigma^2_{\text{Btw Hosp}} = 0.191$ for the cross sectional model, and 0.185 for the time-trend model). The variance component that captures provider-specific variation in the time-trend slope was estimated as zero.

Table 3.2.1c provides the Wald Statistics to determine whether there are statistically significant differences between the vector of parameter estimates generated by each modeling approach. The Wald Statistics consider pair-wise comparisons, and suggest that there were no significant differences between the different modeling approaches for IQI 11.

Table 3.2.1a Parameter Estimates from Cross Sectional Models fit to IQI-11 (Abdominal Aortic Artery Repair Mortality Rate)

Parameter	Simple Logistic Regression Model			Generalized Estimating Equations Model			Generalized Linear Mixed Model		
	Estimate	Std Err	p value	Estimate	Std Err	p value	Estimate	Std Err	p value
Intercept	-1.218	0.258	0.000	-1.198	0.255	0.000	-1.177	0.262	0.000
SEX	0.074	0.184	0.689	0.062	0.181	0.734	0.038	0.188	0.839
AGE1	-0.905	0.111	0.000	-0.898	0.109	0.000	-0.938	0.113	0.000
AGE13	-0.410	0.128	0.001	-0.408	0.125	0.001	-0.431	0.130	0.001
AGE15	0.354	0.199	0.076	0.354	0.196	0.071	0.393	0.203	0.052
AGE27	0.261	0.231	0.259	0.253	0.227	0.265	0.281	0.235	0.233
C2	0.626	1.147	0.585	0.684	1.118	0.541	0.750	1.164	0.519
C3	-0.697	1.063	0.512	-0.645	1.028	0.530	-0.555	1.069	0.604
C4	-0.507	1.075	0.637	-0.403	1.023	0.693	-0.354	1.089	0.745
C5	-3.141	0.299	0.000	-2.979	0.291	0.000	-3.099	0.302	0.000
C6	-2.619	0.272	0.000	-2.487	0.267	0.000	-2.565	0.275	0.000
C7	-0.938	0.254	0.000	-0.893	0.251	0.000	-0.880	0.257	0.001
C8	1.451	0.239	0.000	1.451	0.237	0.000	1.496	0.242	0.000
C9	-1.465	0.243	0.000	-1.366	0.241	0.000	-1.387	0.247	0.000
ρ				0.0073	.	.			
$\sigma^2_{\text{Btw Hosp}}$							0.191	0.043	.

The effect of the *YEAR* parameter (which captures the trend over time) was highly significant for all three modeling approaches, as seen in Table 3.2.1b below.

**Table 3.2.1b Parameter Estimates from Time Trend Models fit to IQI-11
(Abdominal Aortic Artery Repair Mortality Rate)**

Parameter	Simple Logistic Regression Model			Generalized Estimating Equations Model			Generalized Linear Mixed Model		
	Estimate	Std Err	p value	Estimate	Std Err	p value	Estimate	Std Err	p value
Intercept	-1.224	0.258	0.000	-1.203	0.255	0.000	-1.182	0.262	0.000
SEX	0.076	0.184	0.681	0.064	0.181	0.725	0.041	0.187	0.828
AGE1	-0.907	0.111	0.000	-0.900	0.109	0.000	-0.939	0.113	0.000
AGE13	-0.409	0.128	0.001	-0.407	0.125	0.001	-0.429	0.130	0.001
AGE15	0.355	0.199	0.075	0.355	0.196	0.069	0.394	0.203	0.052
AGE27	0.261	0.232	0.260	0.252	0.227	0.267	0.279	0.235	0.235
C2	0.678	1.146	0.554	0.723	1.121	0.519	0.769	1.165	0.509
C3	-0.677	1.062	0.524	-0.629	1.029	0.541	-0.546	1.069	0.609
C4	-0.485	1.075	0.652	-0.381	1.022	0.710	-0.325	1.087	0.765
C5	-3.152	0.299	0.000	-2.990	0.291	0.000	-3.110	0.302	0.000
C6	-2.626	0.272	0.000	-2.496	0.267	0.000	-2.573	0.275	0.000
C7	-0.943	0.254	0.000	-0.897	0.252	0.000	-0.885	0.258	0.001
C8	1.450	0.239	0.000	1.449	0.237	0.000	1.493	0.242	0.000
C9	-1.453	0.243	0.000	-1.357	0.241	0.000	-1.379	0.247	0.000
YEAR	-0.108	0.034	0.001	-0.105	0.035	0.002	-0.101	0.037	0.007
ρ				0.0071	.	.			
σ^2_{Hosp}							0.185	0.043	.
σ^2_{Year}							0.000	.	.

**Table 3.2.1c Wald Test Statistics and (P-Value) Comparing Models fit to IQI-11
(Abdominal Aortic Artery Repair Mortality Rate)**

	Cross Sectional Model			Time Trend Model		
	SLR	GEE	GLMMIX	SLR	GEE	GLMMIX
SLR		7.880 (0.895)	6.21 (0.961)		7.624 (0.938)	6.05 (0.979)
GEE	6.070 (0.965)		2.452 (1.000)	5.907 (0.981)		2.400 (1.000)
GLMMIX	4.117 (0.995)	2.311 (1.000)		4.047 (0.998)	2.260 (1.000)	

* Wald Test uses the estimated covariance matrix from the model listed in each row

3.2.2 Provider-Level Model Predictions

Table 3.2.2 below provides the mean and standard deviation of differences between model predictions (expected rates above the diagonal, and risk-adjusted rates below the diagonal) from a random sample of 50 providers within the NIS reference population for IQI 11. For example, the mean difference in expected rates between the simple logistic regression and GEE approaches for the cross sectional model was 0.004 (relative to a national mean response rate of 0.077 from Table 3.1). Mean differences (and standard deviations) attributable to model specification (simple logistic vs GEE vs GLMMIX) for the risk-adjusted rates appear to be higher than the expected rates.

Table 3.2.2 Estimated Differences (and Standard Deviation) in Provider-Level Model Predictions of Expected and Risk Adjusted Rates for IQI-11 (Abdominal Aortic Artery Repair Mortality Rate)

	Cross Sectional Model			Time Trend Model		
	SLR	GEE	GLMMIX	SLR	GEE	GLMMIX
SLR		-0.004 (0.001)	-0.002 (0.002)		-0.004 (0.001)	-0.002 (0.002)
GEE	0.061 (0.065)		0.001 (0.002)	0.061 (0.068)		0.001 (0.002)
GLMMIX	0.033 (0.032)	-0.028 (0.037)		0.034 (0.034)	-0.027 (0.038)	

* In each 3x3 table above, Expected Rate Differences (and Standard Deviations) are above the diagonal, and Adjusted Rate Differences (and Standard Deviations) are below the diagonal.

3.3 IQI 14 – Hip Replacement Mortality Rate

3.3.1 Model Parameter Estimates

Below we provide the model parameter estimates from fitting the simple logistic regression, generalized estimating equations, and generalized linear mixed model to the 2001-2003 Nationwide Inpatient Sample for IQI 14 (Hip Replacement Mortality Rate). Table 3.3.1a provides the parameter estimates associated with the cross-sectional model, and Table 3.3.1b provides the parameter estimates associated with the model that adjusts for a simple linear trend over time. Across these two tables, we see that the parameter estimates and associated standard errors are identical among the three modeling approaches, with the estimated correlation coefficient from the GEE modeling approach being estimated as zero in both the cross-sectional and time-trend adjusted models. The estimated variance components associated with provider-specific random effects from the GLIMMIX model was also zero in both models, as well as the variance component that captures provider-specific variation in the time-trend slope was estimated as zero.

Table 3.3.1c provides the Wald Statistics to determine whether there are statistically significant differences between the vector of parameter estimates generated by each modeling approach. The Wald Statistics consider pair-wise comparisons, and suggest that there were no significant differences between the different modeling approaches for IQI 14.

**Table 3.3.1a Parameter Estimates from Cross Sectional Models fit to IQI-14
(Hip Replacement Mortality Rate)**

Parameter	Simple Logistic Regression Model			Generalized Estimating Equations Model			Generalized Linear Mixed Model		
	Estimate	Std Err	p value	Estimate	Std Err	p value	Estimate	Std Err	p value
Intercept	-2.377	0.394	0.000	-2.376	0.394	0.000	-2.377	0.394	0.000
SEX	-0.363	0.215	0.091	-0.363	0.215	0.091	-0.363	0.215	0.091
AGE1	-1.573	0.343	0.000	-1.573	0.343	0.000	-1.573	0.343	0.000
AGE10	-1.539	0.404	0.000	-1.539	0.405	0.000	-1.539	0.404	0.000
AGE11	-1.586	0.333	0.000	-1.587	0.333	0.000	-1.586	0.333	0.000
AGE12	-1.017	0.274	0.000	-1.017	0.274	0.000	-1.017	0.274	0.000
AGE13	-0.608	0.252	0.016	-0.608	0.252	0.016	-0.608	0.252	0.016
AGE15	0.549	0.441	0.213	0.549	0.441	0.213	0.549	0.441	0.213
AGE24	0.347	0.543	0.523	0.347	0.543	0.524	0.347	0.543	0.523
AGE25	0.079	0.461	0.865	0.079	0.462	0.864	0.079	0.461	0.865
AGE26	0.142	0.355	0.690	0.141	0.355	0.691	0.142	0.355	0.690
AGE27	-0.092	0.335	0.783	-0.092	0.335	0.783	-0.092	0.335	0.783
C1	-4.016	0.399	0.000	-4.020	0.399	0.000	-4.016	0.399	0.000
C2	-2.260	0.383	0.000	-2.262	0.383	0.000	-2.260	0.383	0.000
C3	0.088	0.378	0.815	0.088	0.378	0.816	0.088	0.378	0.815
C4	2.061	0.384	0.000	2.061	0.384	0.000	2.061	0.384	0.000
C5	0.384	0.559	0.492	0.384	0.559	0.492	0.384	0.559	0.492
ρ				0.0000	.	.			
$\sigma^2_{\text{Btw Hosp}}$							0.000	.	.

The effect of the *YEAR* parameter (which captures the trend over time) was highly significant for all three modeling approaches, as seen in Table 3.3.1b below.

**Table 3.3.1b Parameter Estimates from Time Trend Models fit to IQI-14
(Hip Replacement Mortality Rate)**

Parameter	Simple Logistic Regression Model			Generalized Estimating Equations Model			Generalized Linear Mixed Model		
	Estimate	Std Err	p value	Estimate	Std Err	p value	Estimate	Std Err	p value
Intercept	-2.385	0.394	0.000	-2.385	0.394	0.000	-2.385	0.394	0.000
SEX	-0.372	0.215	0.083	-0.372	0.215	0.083	-0.372	0.215	0.083
AGE1	-1.570	0.343	0.000	-1.571	0.343	0.000	-1.570	0.343	0.000
AGE10	-1.547	0.404	0.000	-1.547	0.405	0.000	-1.547	0.404	0.000
AGE11	-1.595	0.333	0.000	-1.596	0.334	0.000	-1.595	0.333	0.000
AGE12	-1.027	0.275	0.000	-1.027	0.275	0.000	-1.027	0.275	0.000
AGE13	-0.622	0.252	0.014	-0.622	0.253	0.014	-0.622	0.252	0.014
AGE15	0.564	0.441	0.201	0.564	0.442	0.202	0.564	0.441	0.201
AGE24	0.369	0.543	0.497	0.368	0.544	0.498	0.369	0.543	0.497
AGE25	0.089	0.461	0.846	0.090	0.462	0.845	0.089	0.461	0.846
AGE26	0.156	0.355	0.661	0.155	0.355	0.662	0.156	0.355	0.661
AGE27	-0.070	0.335	0.835	-0.070	0.335	0.834	-0.070	0.335	0.835
C1	-4.013	0.399	0.000	-4.019	0.399	0.000	-4.013	0.399	0.000
C2	-2.250	0.384	0.000	-2.252	0.384	0.000	-2.250	0.384	0.000
C3	0.102	0.378	0.788	0.101	0.378	0.789	0.102	0.378	0.788
C4	2.085	0.384	0.000	2.085	0.384	0.000	2.085	0.384	0.000
C5	0.401	0.560	0.474	0.400	0.560	0.475	0.401	0.560	0.474
YEAR	-0.200	0.076	0.009	-0.201	0.076	0.008	-0.200	0.076	0.009
ρ				-0.0001	.	.			
σ^2_{Hosp}							0.000	.	
σ^2_{Year}							0.000	.	

**Table 3.3.1c Wald Test Statistics and (P-Value) Comparing Models fit to IQI-14
(Hip Replacement Mortality Rate)**

	Cross Sectional Model			Time Trend Model		
	SLR	GEE	GLMMIX	SLR	GEE	GLMMIX
SLR		0.001 (1.000)	0.000 (1.000)		0.002 (1.000)	0.000 (1.000)
GEE	0.001 (1.000)		0.001 (1.000)	0.002 (1.000)		0.002 (1.000)
GLMMIX	0.000 (1.000)	0.001 (1.000)		0.000 (1.000)	0.002 (1.000)	

* Wald Test uses the estimated covariance matrix from the model listed in each row

3.3.2 Provider-Level Model Predictions

Table 3.3.2 below provides the mean and standard deviation of differences between model predictions (expected rates above the diagonal, and risk-adjusted rates below the diagonal) from a random sample of 50 providers within the NIS reference population for IQI 14. Due to the fact that the three modeling approaches yielded identical parameter estimates (the within-provider correlation was estimated as zero), there were no differences in expected or risk-adjusted rates attributable to the modeling approach.

Table 3.3.2 Estimated Differences (and Standard Deviation) in Provider-Level Model Predictions of Expected and Risk Adjusted Rates for IQI-14 (Hip Replacement Mortality Rate)

	Cross Sectional Model			Time Trend Model		
	SLR	GEE	GLMMIX	SLR	GEE	GLMMIX
SLR		0.000 (0.000)	0.000 (0.000)		0.000 (0.000)	0.000 (0.000)
GEE	-0.000 (0.000)		0.000 (0.000)	-0.000 (0.000)		0.000 (0.000)
GLMMIX	-0.000 (0.000)	-0.000 (0.000)		-0.000 (0.000)	-0.000 (0.000)	

* In each 3x3 table above, Expected Rate Differences (and Standard Deviations) are above the diagonal, and Adjusted Rate Differences (and Standard Deviations) are below the diagonal.

3.4 IQI 17 – Acute Stroke Mortality Rate

3.4.1 Model Parameter Estimates

Below we provide the model parameter estimates from fitting the simple logistic regression, generalized estimating equations, and generalized linear mixed model to the 2001-2003 Nationwide Inpatient Sample for IQI 17 (Acute Stroke Mortality Rate). Table 3.4.1a provides the parameter estimates associated with the cross-sectional model, and Table 3.4.1b provides the parameter estimates associated with the model that adjusts for a simple linear trend over time. Across these two tables, we see that the parameter estimates and associated standard errors are comparable among the three modeling approaches (but with noticeable differences). In this model, the estimated correlation coefficient from the GEE modeling approach is nearly zero in both the cross-sectional ($\rho=0.0082$) and time-trend adjusted ($\rho=0.0079$) models. The estimated variance components associated with provider-specific random effects from the GLMMIX model were small, yet statistically significant in both models ($\sigma^2_{\text{Btw Hosp}} = 0.173$ for the cross sectional model, and 0.161 for the time-trend model). The variance component that captures provider-specific variation in the time-trend slope was estimated as statistically significant ($\sigma^2_{\text{Year}} = 0.019$).

The effect of the *YEAR* parameter (which captures the trend over time) was highly significant for all three modeling approaches, as seen in Table 3.4.1b below.

Table 3.4.1c provides the Wald Statistics to determine whether there are statistically significant differences between the vector of parameter estimates generated by each modeling approach. The Wald Statistics consider pair-wise comparisons, and suggest that there were significant differences between the different modeling approaches for IQI 17. In fact, the first row of Table 3.2.1c suggests that there are highly significant differences between the parameter estimates from the simple logistic regression model compared to both approaches (GEE and GLMMIX) that adjust for the potential within-hospital correlation among responses. This first row corresponds to a Wald Test that uses the estimated variance/covariance matrix from the simple logistic regression model. The corresponding Wald-Statistic Results that utilize the variance-covariance matrices from the GEE or GLMMIX approaches are contained in the SLR columns (on each side of the table) – and interestingly enough do not meet the threshold of being significantly different. These variance/covariance matrices are model-based and may be subject to model misspecification. A subsequent iteration of this report will integrate similar Wald Test statistics using the robust variance/covariance estimates for the GEE and GLMMIX approaches.

Another interesting phenomenon is that there are statistically significant differences between the GEE and GLMMIX approaches (for both the cross-sectional and time-trend models). Again, this result necessitates further diagnoses of the fit of these models.

**Table 3.4.1a Parameter Estimates from Cross Sectional Models fit to IQI-17
(Acute Stroke Mortality Rate)**

Parameter	Simple Logistic Regression Model			Generalized Estimating Equations Model			Generalized Linear Mixed Model		
	Estimate	Std Err	p value	Estimate	Std Err	p value	Estimate	Std Err	p value
Intercept	-1.727	0.068	0.000	-1.655	0.066	0.000	-1.660	0.069	0.000
SEX	0.067	0.028	0.018	0.063	0.028	0.024	0.063	0.028	0.028
AGE1	-0.951	0.177	0.000	-0.910	0.173	0.000	-0.945	0.180	0.000
AGE2	-0.994	0.168	0.000	-0.935	0.163	0.000	-0.952	0.170	0.000
AGE3	-0.682	0.110	0.000	-0.640	0.107	0.000	-0.663	0.112	0.000
AGE4	-0.663	0.090	0.000	-0.619	0.088	0.000	-0.636	0.091	0.000
AGE5	-0.669	0.068	0.000	-0.636	0.067	0.000	-0.662	0.069	0.000
AGE6	-0.472	0.055	0.000	-0.439	0.054	0.000	-0.454	0.056	0.000
AGE7	-0.483	0.049	0.000	-0.454	0.048	0.000	-0.473	0.049	0.000
AGE8	-0.453	0.047	0.000	-0.421	0.046	0.000	-0.437	0.048	0.000
AGE9	-0.442	0.044	0.000	-0.411	0.043	0.000	-0.422	0.045	0.000
AGE10	-0.375	0.040	0.000	-0.352	0.039	0.000	-0.362	0.041	0.000
AGE11	-0.419	0.037	0.000	-0.393	0.036	0.000	-0.405	0.037	0.000
AGE12	-0.329	0.034	0.000	-0.311	0.033	0.000	-0.320	0.035	0.000
AGE13	-0.208	0.034	0.000	-0.197	0.033	0.000	-0.205	0.034	0.000
AGE15	-0.366	0.279	0.190	-0.336	0.271	0.215	-0.336	0.284	0.236
AGE16	-0.211	0.252	0.403	-0.203	0.244	0.405	-0.235	0.255	0.356
AGE17	-0.304	0.162	0.060	-0.287	0.157	0.068	-0.292	0.163	0.075
AGE18	-0.252	0.129	0.051	-0.243	0.126	0.053	-0.258	0.131	0.048
AGE19	0.126	0.093	0.177	0.127	0.091	0.163	0.134	0.094	0.155
AGE20	-0.114	0.077	0.140	-0.107	0.075	0.155	-0.110	0.078	0.160
AGE21	-0.149	0.069	0.030	-0.131	0.067	0.049	-0.125	0.069	0.073
AGE22	-0.150	0.066	0.023	-0.149	0.064	0.021	-0.152	0.067	0.022
AGE23	-0.049	0.062	0.425	-0.050	0.060	0.408	-0.051	0.062	0.411
AGE24	-0.138	0.055	0.013	-0.134	0.054	0.013	-0.139	0.056	0.013
AGE25	-0.014	0.048	0.764	-0.018	0.047	0.700	-0.018	0.049	0.716
AGE26	-0.045	0.044	0.301	-0.041	0.043	0.342	-0.039	0.044	0.380
AGE27	-0.087	0.042	0.039	-0.083	0.041	0.044	-0.083	0.042	0.050
C1	-1.548	0.140	0.000	-1.465	0.130	0.000	-1.558	0.141	0.000
C2	-0.111	0.082	0.175	-0.113	0.079	0.154	-0.114	0.083	0.169
C3	1.019	0.070	0.000	0.986	0.068	0.000	1.022	0.071	0.000
C4	2.289	0.074	0.000	2.260	0.072	0.000	2.341	0.075	0.000
C5	-0.211	0.085	0.013	-0.222	0.082	0.007	-0.236	0.086	0.006
C6	0.411	0.066	0.000	0.377	0.064	0.000	0.383	0.067	0.000
C7	1.578	0.068	0.000	1.535	0.066	0.000	1.580	0.069	0.000
C8	3.312	0.068	0.000	3.290	0.066	0.000	3.375	0.069	0.000
C9	-2.565	0.077	0.000	-2.425	0.074	0.000	-2.610	0.077	0.000
C10	-1.224	0.066	0.000	-1.204	0.064	0.000	-1.264	0.067	0.000
C11	0.295	0.067	0.000	0.277	0.064	0.000	0.284	0.067	0.000
C12	2.126	0.067	0.000	2.089	0.065	0.000	2.152	0.067	0.000
C13	-2.451	0.094	0.000	-2.387	0.090	0.000	-2.525	0.095	0.000
C14	-0.958	0.068	0.000	-0.984	0.066	0.000	-1.030	0.069	0.000
C15	0.359	0.072	0.000	0.315	0.070	0.000	0.315	0.073	0.000
C16	2.031	0.078	0.000	1.987	0.076	0.000	2.047	0.079	0.000
C17	-0.014	0.072	0.843	-0.010	0.069	0.880	-0.007	0.073	0.922
ρ				0.0082	.	.			
σ^2_{Hosp}							0.173	0.011	.

**Table 3.4.1b Parameter Estimates from Time Trend Models fit to IQI-17
(Acute Stroke Mortality Rate)**

Parameter	Simple Logistic Regression Model			Generalized Estimating Equations Model			Generalized Linear Mixed Model		
	Estimate	Std Err	p value	Estimate	Std Err	p value	Estimate	Std Err	p value
Intercept	-1.725	0.068	0.000	-1.656	0.066	0.000	-1.662	0.069	0.000
SEX	0.066	0.028	0.020	0.062	0.028	0.025	0.062	0.028	0.029
AGE1	-0.951	0.177	0.000	-0.913	0.173	0.000	-0.944	0.180	0.000
AGE2	-0.990	0.168	0.000	-0.936	0.163	0.000	-0.951	0.170	0.000
AGE3	-0.681	0.110	0.000	-0.640	0.107	0.000	-0.664	0.112	0.000
AGE4	-0.661	0.090	0.000	-0.620	0.088	0.000	-0.638	0.091	0.000
AGE5	-0.669	0.068	0.000	-0.637	0.067	0.000	-0.663	0.069	0.000
AGE6	-0.468	0.055	0.000	-0.438	0.054	0.000	-0.454	0.056	0.000
AGE7	-0.480	0.049	0.000	-0.453	0.048	0.000	-0.474	0.049	0.000
AGE8	-0.451	0.047	0.000	-0.421	0.046	0.000	-0.438	0.048	0.000
AGE9	-0.441	0.045	0.000	-0.412	0.043	0.000	-0.423	0.045	0.000
AGE10	-0.375	0.040	0.000	-0.353	0.039	0.000	-0.363	0.041	0.000
AGE11	-0.420	0.037	0.000	-0.395	0.036	0.000	-0.405	0.037	0.000
AGE12	-0.331	0.034	0.000	-0.313	0.033	0.000	-0.322	0.035	0.000
AGE13	-0.209	0.034	0.000	-0.198	0.033	0.000	-0.205	0.034	0.000
AGE15	-0.352	0.279	0.207	-0.326	0.271	0.229	-0.334	0.284	0.240
AGE16	-0.207	0.252	0.411	-0.201	0.244	0.410	-0.232	0.255	0.363
AGE17	-0.307	0.162	0.058	-0.290	0.158	0.066	-0.291	0.164	0.075
AGE18	-0.257	0.129	0.046	-0.246	0.126	0.050	-0.258	0.131	0.048
AGE19	0.129	0.093	0.167	0.129	0.091	0.157	0.135	0.094	0.154
AGE20	-0.113	0.077	0.142	-0.107	0.075	0.156	-0.110	0.078	0.160
AGE21	-0.150	0.069	0.029	-0.132	0.067	0.049	-0.123	0.069	0.076
AGE22	-0.150	0.066	0.023	-0.149	0.064	0.021	-0.152	0.067	0.023
AGE23	-0.048	0.062	0.433	-0.049	0.060	0.415	-0.050	0.062	0.424
AGE24	-0.137	0.055	0.013	-0.133	0.054	0.014	-0.139	0.056	0.013
AGE25	-0.014	0.048	0.770	-0.018	0.047	0.705	-0.018	0.049	0.708
AGE26	-0.044	0.044	0.317	-0.040	0.043	0.354	-0.038	0.044	0.386
AGE27	-0.086	0.042	0.039	-0.083	0.041	0.044	-0.083	0.042	0.049
C1	-1.550	0.140	0.000	-1.468	0.130	0.000	-1.558	0.141	0.000
C2	-0.112	0.082	0.173	-0.113	0.079	0.155	-0.113	0.083	0.174
C3	1.016	0.070	0.000	0.986	0.068	0.000	1.021	0.071	0.000
C4	2.291	0.074	0.000	2.264	0.072	0.000	2.344	0.075	0.000
C5	-0.210	0.085	0.014	-0.221	0.082	0.007	-0.234	0.086	0.006
C6	0.409	0.066	0.000	0.378	0.064	0.000	0.383	0.067	0.000
C7	1.579	0.068	0.000	1.538	0.066	0.000	1.582	0.069	0.000
C8	3.314	0.068	0.000	3.293	0.066	0.000	3.378	0.069	0.000
C9	-2.568	0.077	0.000	-2.429	0.074	0.000	-2.609	0.077	0.000
C10	-1.225	0.066	0.000	-1.204	0.064	0.000	-1.263	0.067	0.000
C11	0.297	0.067	0.000	0.280	0.065	0.000	0.286	0.067	0.000
C12	2.128	0.067	0.000	2.093	0.065	0.000	2.155	0.067	0.000
C13	-2.458	0.094	0.000	-2.391	0.090	0.000	-2.526	0.095	0.000
C14	-0.965	0.068	0.000	-0.987	0.066	0.000	-1.030	0.069	0.000
C15	0.353	0.072	0.000	0.313	0.070	0.000	0.314	0.073	0.000
C16	2.026	0.078	0.000	1.986	0.076	0.000	2.047	0.079	0.000
C17	-0.011	0.072	0.874	-0.009	0.070	0.901	-0.005	0.073	0.945
YEAR	-0.065	0.008	0.000	-0.053	0.010	0.000	-0.059	0.013	0.000
ρ				0.0079	.	.			
σ^2_{Hosp}							0.161	0.011	.
σ^2_{Year}							0.019	0.007	.

**Table 3.4.1c Wald Test Statistics and (P-Value) Comparing Models fit to IQI-17
(Acute Stroke Mortality Rate)**

	Cross Sectional Model			Time Trend Model		
	SLR	GEE	GLMMIX	SLR	GEE	GLMMIX
SLR		154.85 (0.000)	127.77 (0.000)		149.27 (0.000)	120.62 (0.000)
GEE	57.362 (0.102)		64.972 (0.027)	56.246 (0.143)		62.365 (0.054)
GLMMIX	49.287 (0.306)	70.869 (0.008)		46.309 (0.460)	68.044 (0.019)	

* Wald Test uses the estimated covariance matrix from the model listed in each row

3.4.2 Provider-Level Model Predictions

Table 3.4.2 below provides the mean and standard deviation of differences between model predictions (expected rates above the diagonal, and risk-adjusted rates below the diagonal) from a random sample of 50 providers within the NIS reference population for IQI 17. For example, the mean difference in expected rates between the simple logistic regression and GEE approaches for the cross sectional model was -0.006 (relative to a national mean response rate of 0.114 from Table 3.1). Mean differences (and standard deviations) attributable to model specification (simple logistic vs GEE vs GLMMIX) for the risk-adjusted rates appear to be higher than the expected rates.

**Table 3.4.2 Estimated Differences (and Standard Deviation) in Provider-Level
Model Predictions of Expected and Risk Adjusted Rates for IQI-17
(Acute Stroke Mortality Rate)**

	Cross Sectional Model			Time Trend Model		
	SLR	GEE	GLMMIX	SLR	GEE	GLMMIX
SLR		-0.006 (0.001)	-0.002 (0.001)		-0.005 (0.001)	-0.002 (0.001)
GEE	0.021 (0.015)		0.004 (0.000)	0.021 (0.015)		0.004 (0.001)
GLMMIX	0.007 (0.004)	-0.014 (0.011)		0.007 (0.005)	-0.014 (0.011)	

* In each 3x3 table above, Expected Rate Differences (and Standard Deviations) are above the diagonal, and Adjusted Rate Differences (and Standard Deviations) are below the diagonal.

3.5 IQI 19 – Hip Fracture Mortality Rate

3.5.1 Model Parameter Estimates

Below we provide the model parameter estimates from fitting the simple logistic regression, generalized estimating equations, and generalized linear mixed model to the 2001-2003 Nationwide Inpatient Sample for IQI 19 (Hip Fracture Mortality Rate). Table 3.5.1a provides the parameter estimates associated with the cross-sectional model, and Table 3.5.1b provides the parameter estimates associated with the model that adjusts for a simple linear trend over time. Across these two tables, we see that the parameter estimates and associated standard errors are quite comparable among the three modeling approaches. In fact, the estimated correlation coefficient from the GEE modeling approach is nearly zero ($\rho=0.0017$) in both the cross-sectional and time-trend adjusted models. The estimated variance components associated with provider-specific random effects from the GLIMMIX model were subtle, yet statistically significant in both models ($\sigma^2_{\text{Btw Hosp}} = 0.126$ for the cross sectional model, and 0.109 for the time-trend model). The variance component that captures provider-specific variation in the time-trend slope was statistically significant ($\sigma^2_{\text{year}} = 0.043$).

Table 3.5.1c provides the Wald Statistics to determine whether there are statistically significant differences between the vector of parameter estimates generated by each modeling approach. The Wald Statistics consider pair-wise comparisons, and suggest that there were no significant differences between the different modeling approaches for IQI 19.

**Table 3.5.1a Parameter Estimates from Cross Sectional Models fit to IQI-19
(Hip Fracture Mortality Rate)**

Parameter	Simple Logistic Regression Model			Generalized Estimating Equations Model			Generalized Linear Mixed Model		
	Estimate	Std Err	p value	Estimate	Std Err	p value	Estimate	Std Err	p value
Intercept	-1.569	0.139	0.000	-1.565	0.139	0.000	-1.560	0.141	0.000
SEX	-0.310	0.043	0.000	-0.310	0.043	0.000	-0.317	0.044	0.000
AGE3	-2.610	1.007	0.010	-2.569	0.979	0.009	-2.609	1.008	0.010
AGE4	-1.244	0.459	0.007	-1.224	0.452	0.007	-1.233	0.461	0.007
AGE5	-2.137	0.587	0.000	-2.131	0.580	0.000	-2.167	0.588	0.000
AGE6	-0.905	0.271	0.001	-0.912	0.269	0.001	-0.955	0.273	0.000
AGE7	-0.729	0.224	0.001	-0.728	0.222	0.001	-0.732	0.225	0.001
AGE8	-0.860	0.225	0.000	-0.853	0.223	0.000	-0.866	0.226	0.000
AGE9	-0.525	0.170	0.002	-0.524	0.169	0.002	-0.546	0.172	0.001
AGE10	-0.453	0.122	0.000	-0.454	0.122	0.000	-0.462	0.123	0.000
AGE11	-0.713	0.096	0.000	-0.711	0.096	0.000	-0.721	0.097	0.000
AGE12	-0.449	0.071	0.000	-0.448	0.071	0.000	-0.453	0.072	0.000
AGE13	-0.296	0.061	0.000	-0.293	0.061	0.000	-0.293	0.062	0.000
AGE17	1.740	1.245	0.162	1.703	1.219	0.162	1.744	1.248	0.162
AGE18	-0.155	1.109	0.889	-0.167	1.094	0.879	-0.173	1.110	0.876
AGE19	0.950	0.835	0.256	0.951	0.826	0.249	0.965	0.837	0.249
AGE20	0.687	0.420	0.102	0.690	0.418	0.099	0.746	0.422	0.077
AGE21	-0.103	0.376	0.785	-0.098	0.373	0.793	-0.099	0.378	0.794
AGE22	0.437	0.310	0.159	0.430	0.307	0.161	0.446	0.311	0.152
AGE23	0.345	0.232	0.137	0.348	0.230	0.131	0.376	0.234	0.108
AGE24	-0.053	0.171	0.755	-0.048	0.170	0.776	-0.046	0.172	0.788
AGE25	0.141	0.124	0.256	0.140	0.123	0.255	0.135	0.125	0.279
AGE26	-0.078	0.093	0.401	-0.074	0.092	0.420	-0.078	0.093	0.405
AGE27	-0.074	0.077	0.339	-0.073	0.077	0.340	-0.078	0.078	0.313
C1	-3.211	0.166	0.000	-3.191	0.166	0.000	-3.223	0.167	0.000
C2	-2.221	0.145	0.000	-2.204	0.145	0.000	-2.224	0.146	0.000
C3	-0.330	0.142	0.020	-0.325	0.142	0.022	-0.325	0.143	0.023
C4	1.293	0.145	0.000	1.298	0.145	0.000	1.328	0.146	0.000
C5	-3.925	0.169	0.000	-3.886	0.169	0.000	-3.930	0.170	0.000
C6	-2.462	0.143	0.000	-2.440	0.143	0.000	-2.461	0.144	0.000
C7	-0.377	0.140	0.007	-0.369	0.140	0.008	-0.365	0.141	0.010
C8	1.427	0.143	0.000	1.431	0.143	0.000	1.458	0.145	0.000
C9	-1.960	0.177	0.000	-1.928	0.175	0.000	-1.920	0.178	0.000
C10	-0.639	0.146	0.000	-0.623	0.145	0.000	-0.597	0.147	0.000
C11	1.058	0.145	0.000	1.063	0.145	0.000	1.097	0.147	0.000
C12	2.582	0.161	0.000	2.584	0.161	0.000	2.620	0.163	0.000
C13	-0.502	0.152	0.001	-0.492	0.152	0.001	-0.483	0.153	0.002
ρ				0.0017	.	.			
σ^2_{Hosp}							0.126	0.017	.

The effect of the *YEAR* parameter (which captures the trend over time) was highly significant for all three modeling approaches, as seen in Table 3.5.1b below.

**Table 3.5.1b Parameter Estimates from Time Trend Models fit to IQI-19
(Hip Fracture Mortality Rate)**

Parameter	Simple Logistic Regression Model			Generalized Estimating Equations Model			Generalized Linear Mixed Model		
	Estimate	Std Err	p value	Estimate	Std Err	p value	Estimate	Std Err	p value
Intercept	-1.570	0.139	0.000	-1.567	0.139	0.000	-1.566	0.141	0.000
SEX	-0.311	0.043	0.000	-0.311	0.043	0.000	-0.318	0.044	0.000
AGE3	-2.609	1.007	0.010	-2.570	0.980	0.009	-2.618	1.008	0.009
AGE4	-1.242	0.460	0.007	-1.222	0.452	0.007	-1.230	0.461	0.008
AGE5	-2.141	0.587	0.000	-2.135	0.581	0.000	-2.177	0.588	0.000
AGE6	-0.897	0.270	0.001	-0.903	0.269	0.001	-0.949	0.273	0.001
AGE7	-0.727	0.224	0.001	-0.725	0.222	0.001	-0.731	0.225	0.001
AGE8	-0.858	0.225	0.000	-0.851	0.223	0.000	-0.866	0.226	0.000
AGE9	-0.521	0.170	0.002	-0.520	0.169	0.002	-0.546	0.172	0.001
AGE10	-0.448	0.122	0.000	-0.449	0.122	0.000	-0.458	0.123	0.000
AGE11	-0.714	0.096	0.000	-0.713	0.096	0.000	-0.722	0.097	0.000
AGE12	-0.447	0.071	0.000	-0.446	0.071	0.000	-0.454	0.072	0.000
AGE13	-0.296	0.061	0.000	-0.293	0.061	0.000	-0.293	0.062	0.000
AGE17	1.751	1.246	0.160	1.715	1.220	0.160	1.770	1.248	0.156
AGE18	-0.159	1.109	0.886	-0.170	1.093	0.876	-0.170	1.110	0.879
AGE19	0.952	0.836	0.254	0.954	0.826	0.248	0.975	0.837	0.244
AGE20	0.682	0.420	0.105	0.685	0.418	0.101	0.747	0.422	0.077
AGE21	-0.107	0.376	0.777	-0.102	0.373	0.785	-0.099	0.378	0.794
AGE22	0.443	0.310	0.152	0.437	0.307	0.154	0.452	0.311	0.146
AGE23	0.347	0.232	0.135	0.350	0.230	0.129	0.380	0.234	0.105
AGE24	-0.059	0.171	0.729	-0.054	0.170	0.750	-0.049	0.172	0.778
AGE25	0.143	0.124	0.249	0.142	0.123	0.249	0.137	0.125	0.272
AGE26	-0.079	0.093	0.393	-0.075	0.092	0.413	-0.077	0.093	0.408
AGE27	-0.074	0.077	0.339	-0.073	0.077	0.340	-0.077	0.078	0.320
C1	-3.213	0.166	0.000	-3.192	0.166	0.000	-3.221	0.168	0.000
C2	-2.220	0.145	0.000	-2.204	0.145	0.000	-2.219	0.146	0.000
C3	-0.326	0.142	0.022	-0.321	0.142	0.024	-0.317	0.143	0.027
C4	1.299	0.145	0.000	1.304	0.145	0.000	1.338	0.146	0.000
C5	-3.927	0.169	0.000	-3.887	0.169	0.000	-3.928	0.170	0.000
C6	-2.461	0.143	0.000	-2.439	0.143	0.000	-2.456	0.144	0.000
C7	-0.374	0.140	0.008	-0.366	0.140	0.009	-0.358	0.142	0.012
C8	1.433	0.143	0.000	1.437	0.143	0.000	1.468	0.145	0.000
C9	-1.966	0.177	0.000	-1.933	0.175	0.000	-1.919	0.178	0.000
C10	-0.641	0.146	0.000	-0.625	0.145	0.000	-0.592	0.147	0.000
C11	1.057	0.145	0.000	1.062	0.145	0.000	1.102	0.147	0.000
C12	2.589	0.161	0.000	2.592	0.161	0.000	2.634	0.163	0.000
C13	-0.501	0.152	0.001	-0.490	0.152	0.001	-0.478	0.154	0.002
YEAR	-0.063	0.018	0.001	-0.066	0.019	0.000	-0.066	0.021	0.002
ρ				0.0017	.	.			
σ^2_{Hosp}							0.109	0.018	.
σ^2_{Year}							0.043	0.019	.

**Table 3.5.1c Wald Test Statistics and (P-Value) Comparing Models fit to IQI-19
(Hip Fracture Mortality Rate)**

	Cross Sectional Model			Time Trend Model		
	SLR	GEE	GLMMIX	SLR	GEE	GLMMIX
SLR		1.473 (1.000)	3.396 (1.000)		1.557 (1.000)	3.440 (1.000)
GEE	1.178 (1.000)		2.391 (1.000)	1.252 (1.000)		2.509 (1.000)
GLMMIX	2.614 (1.000)	2.332 (1.000)		2.696 (1.000)	2.470 (1.000)	

* Wald Test uses the estimated covariance matrix from the model listed in each row

3.5.2 Provider-Level Model Predictions

Table 3.4.2 below provides the mean and standard deviation of differences between model predictions (expected rates above the diagonal, and risk-adjusted rates below the diagonal) from a random sample of 50 providers within the NIS reference population for IQI 17. The mean difference in expected rates and risk-adjusted rates was nearly zero for all modeling approach pairwise comparisons – despite the fact that the GLMMIX modeling approaches identified statistically significant variance components associated with the random effects.

**Table 3.5.2 Estimated Differences (and Standard Deviation) in Provider-Level
Model Predictions of Expected and Risk Adjusted Rates for IQI-19
(Hip Fracture Mortality Rate)**

	Cross Sectional Model			Time Trend Model		
	SLR	GEE	GLMMIX	SLR	GEE	GLMMIX
SLR		-0.000 (0.000)	-0.000 (0.001)		-0.000 (0.000)	-0.000 (0.001)
GEE	0.004 (0.006)		0.000 (0.000)	0.004 (0.006)		0.000 (0.000)
GLMMIX	0.001 (0.005)	-0.003 (0.005)		0.001 (0.005)	-0.003 (0.006)	

* In each 3x3 table above, Expected Rate Differences (and Standard Deviations) are above the diagonal, and Adjusted Rate Differences (and Standard Deviations) are below the diagonal.

3.6 IQI 25 – Bilateral Cardiac Catheterization Rate

3.6.1 Model Parameter Estimates

Below we provide the model parameter estimates from fitting the simple logistic regression, generalized estimating equations, and generalized linear mixed model to the 2001-2003 Nationwide Inpatient Sample for IQI 25 (Bilateral Cardiac Catheterization Rate). Table 3.6.1a provides the parameter estimates associated with the cross-sectional model, and Table 3.6.1b provides the parameter estimates associated with the model that adjusts for a simple linear trend over time. Across these two tables, we see that the parameter estimates and associated standard errors are comparable, but with noticeable differences among the three modeling approaches. The estimated correlation coefficient from the GEE modeling approach was largest for this Quality Indicator (compared to the other four QIs investigated), with $\rho=0.0412$ in the cross-sectional and $\rho=0.0405$ in the time-trend adjusted model. The estimated variance components associated with provider-specific random effects from the GLIMMIX model were also comparatively larger, and statistically significant in both models ($\sigma^2_{\text{Btw Hosp}} = 0.779$ for the cross sectional model, and 0.766 for the time-trend model). The variance component that captures provider-specific variation in the time-trend slope was statistically significant ($\sigma^2_{\text{Year}} = 0.031$).

The effect of the *YEAR* parameter (which captures the trend over time) was highly significant for all three modeling approaches, as seen in Table 3.6.1b below.

Table 3.6.1c provides the Wald Statistics to determine whether there are statistically significant differences between the vector of parameter estimates generated by each modeling approach. The Wald Statistics consider pair-wise comparisons, and suggest that there were highly significant differences between the different modeling approaches for IQI 25.

**Table 3.6.1a Parameter Estimates from Cross Sectional Models fit to IQI-25
(Bilateral Cardiac Catheterization Rate)**

Parameter	Simple Logistic Regression Model			Generalized Estimating Equations Model			Generalized Linear Mixed Model		
	Estimate	Std Err	p value	Estimate	Std Err	p value	Estimate	Std Err	p value
Intercept	-1.820	0.038	0.000	-1.871	0.042	0.000	-2.169	0.050	0.000
SEX	-0.115	0.036	0.001	-0.121	0.036	0.001	-0.127	0.038	0.001
AGE1	-0.307	0.214	0.152	-0.283	0.209	0.174	-0.273	0.222	0.219
AGE2	-0.556	0.158	0.000	-0.465	0.150	0.002	-0.499	0.163	0.002
AGE3	-0.829	0.089	0.000	-0.687	0.083	0.000	-0.751	0.092	0.000
AGE4	-0.964	0.061	0.000	-0.830	0.058	0.000	-0.907	0.063	0.000
AGE5	-0.903	0.043	0.000	-0.771	0.041	0.000	-0.840	0.044	0.000
AGE6	-0.850	0.036	0.000	-0.722	0.035	0.000	-0.787	0.037	0.000
AGE7	-0.765	0.033	0.000	-0.640	0.032	0.000	-0.694	0.034	0.000
AGE8	-0.591	0.031	0.000	-0.500	0.031	0.000	-0.537	0.033	0.000
AGE9	-0.472	0.031	0.000	-0.385	0.030	0.000	-0.410	0.032	0.000
AGE10	-0.308	0.030	0.000	-0.238	0.029	0.000	-0.248	0.031	0.000
AGE11	-0.212	0.030	0.000	-0.153	0.029	0.000	-0.155	0.031	0.000
AGE12	-0.072	0.030	0.015	-0.037	0.029	0.202	-0.031	0.031	0.315
AGE13	0.002	0.031	0.941	0.021	0.031	0.492	0.029	0.033	0.367
AGE15	0.555	0.366	0.129	0.469	0.364	0.197	0.462	0.385	0.230
AGE16	0.473	0.259	0.067	0.456	0.247	0.065	0.492	0.267	0.066
AGE17	0.251	0.165	0.128	0.239	0.154	0.120	0.268	0.170	0.116
AGE18	0.277	0.104	0.008	0.283	0.097	0.004	0.302	0.107	0.005
AGE19	0.278	0.070	0.000	0.297	0.065	0.000	0.323	0.072	0.000
AGE20	0.299	0.056	0.000	0.295	0.053	0.000	0.321	0.058	0.000
AGE21	0.221	0.049	0.000	0.210	0.048	0.000	0.229	0.051	0.000
AGE22	0.126	0.046	0.006	0.148	0.045	0.001	0.160	0.048	0.001
AGE23	0.152	0.044	0.001	0.162	0.043	0.000	0.177	0.046	0.000
AGE24	0.057	0.043	0.180	0.079	0.042	0.059	0.084	0.045	0.059
AGE25	0.070	0.042	0.094	0.084	0.041	0.039	0.089	0.043	0.041
AGE26	0.034	0.041	0.408	0.055	0.040	0.173	0.058	0.043	0.175
AGE27	-0.045	0.043	0.300	-0.022	0.042	0.601	-0.028	0.045	0.543
C1	-1.333	0.063	0.000	-1.119	0.058	0.000	-1.263	0.064	0.000
C2	-0.980	0.034	0.000	-0.822	0.034	0.000	-0.916	0.036	0.000
C3	-0.123	0.033	0.000	-0.079	0.032	0.014	-0.088	0.034	0.011
C4	0.218	0.041	0.000	0.275	0.039	0.000	0.298	0.043	0.000
C5	-1.340	0.032	0.000	-1.191	0.035	0.000	-1.319	0.034	0.000
C6	-0.658	0.031	0.000	-0.576	0.030	0.000	-0.634	0.032	0.000
C7	0.159	0.035	0.000	0.169	0.034	0.000	0.177	0.036	0.000
C8	0.548	0.054	0.000	0.544	0.052	0.000	0.570	0.056	0.000
C9	-1.019	0.049	0.000	-0.939	0.048	0.000	-1.033	0.050	0.000
C10	-0.451	0.035	0.000	-0.379	0.034	0.000	-0.415	0.036	0.000
C11	0.268	0.037	0.000	0.307	0.036	0.000	0.343	0.038	0.000
C12	0.836	0.041	0.000	0.860	0.040	0.000	0.947	0.043	0.000
C13	0.638	0.039	0.000	0.625	0.038	0.000	0.681	0.041	0.000
C14	0.491	0.037	0.000	0.502	0.036	0.000	0.555	0.038	0.000
C15	0.921	0.031	0.000	0.907	0.031	0.000	0.995	0.032	0.000
C16	1.032	0.053	0.000	1.028	0.052	0.000	1.128	0.055	0.000
C17	-0.954	0.032	0.000	-0.933	0.033	0.000	-1.014	0.033	0.000
C18	-0.308	0.031	0.000	-0.282	0.030	0.000	-0.309	0.032	0.000
C19	0.214	0.036	0.000	0.202	0.036	0.000	0.219	0.038	0.000
C20	0.628	0.080	0.000	0.612	0.079	0.000	0.652	0.084	0.000
C21	-0.068	0.028	0.017	-0.008	0.028	0.761	-0.010	0.030	0.738
ρ				0.0412	.	.			
σ^2_{Hosp}							0.779	0.041	.

**Table 3.6.1b Parameter Estimates from Time Trend Models fit to IQI-25
(Bilateral Cardiac Catheterization Rate)**

Parameter	Simple Logistic Regression Model			Generalized Estimating Equations Model			Generalized Linear Mixed Model		
	Estimate	Std Err	p value	Estimate	Std Err	p value	Estimate	Std Err	p value
Intercept	-1.817	0.038	0.000	-1.870	0.042	0.000	-2.167	0.050	0.000
SEX	-0.116	0.036	0.001	-0.122	0.036	0.001	-0.130	0.038	0.001
AGE1	-0.298	0.215	0.165	-0.277	0.209	0.184	-0.263	0.222	0.236
AGE2	-0.549	0.158	0.001	-0.464	0.150	0.002	-0.499	0.163	0.002
AGE3	-0.824	0.089	0.000	-0.688	0.083	0.000	-0.755	0.092	0.000
AGE4	-0.963	0.061	0.000	-0.832	0.058	0.000	-0.908	0.063	0.000
AGE5	-0.901	0.043	0.000	-0.773	0.041	0.000	-0.844	0.044	0.000
AGE6	-0.847	0.036	0.000	-0.723	0.035	0.000	-0.788	0.037	0.000
AGE7	-0.764	0.033	0.000	-0.642	0.032	0.000	-0.696	0.034	0.000
AGE8	-0.589	0.031	0.000	-0.500	0.031	0.000	-0.539	0.033	0.000
AGE9	-0.470	0.031	0.000	-0.386	0.030	0.000	-0.411	0.032	0.000
AGE10	-0.308	0.030	0.000	-0.240	0.029	0.000	-0.250	0.031	0.000
AGE11	-0.213	0.030	0.000	-0.154	0.029	0.000	-0.157	0.031	0.000
AGE12	-0.072	0.030	0.015	-0.038	0.029	0.190	-0.032	0.031	0.298
AGE13	0.003	0.031	0.935	0.020	0.031	0.503	0.028	0.033	0.384
AGE15	0.568	0.366	0.121	0.475	0.365	0.192	0.462	0.385	0.230
AGE16	0.475	0.259	0.066	0.458	0.248	0.064	0.504	0.267	0.060
AGE17	0.250	0.165	0.130	0.239	0.154	0.121	0.275	0.170	0.106
AGE18	0.279	0.104	0.008	0.286	0.097	0.003	0.301	0.108	0.005
AGE19	0.281	0.070	0.000	0.298	0.065	0.000	0.328	0.072	0.000
AGE20	0.301	0.056	0.000	0.297	0.054	0.000	0.323	0.058	0.000
AGE21	0.222	0.049	0.000	0.211	0.048	0.000	0.232	0.051	0.000
AGE22	0.127	0.046	0.006	0.149	0.045	0.001	0.163	0.048	0.001
AGE23	0.154	0.044	0.001	0.163	0.043	0.000	0.179	0.046	0.000
AGE24	0.058	0.043	0.175	0.080	0.042	0.056	0.086	0.045	0.053
AGE25	0.070	0.042	0.090	0.084	0.041	0.038	0.091	0.043	0.037
AGE26	0.034	0.041	0.408	0.055	0.040	0.172	0.060	0.043	0.165
AGE27	-0.045	0.043	0.303	-0.022	0.043	0.610	-0.026	0.045	0.573
C1	-1.343	0.063	0.000	-1.122	0.058	0.000	-1.266	0.064	0.000
C2	-0.987	0.034	0.000	-0.826	0.034	0.000	-0.919	0.036	0.000
C3	-0.128	0.033	0.000	-0.081	0.032	0.011	-0.090	0.034	0.009
C4	0.215	0.041	0.000	0.273	0.040	0.000	0.298	0.043	0.000
C5	-1.345	0.032	0.000	-1.192	0.035	0.000	-1.320	0.034	0.000
C6	-0.660	0.031	0.000	-0.576	0.030	0.000	-0.632	0.032	0.000
C7	0.158	0.035	0.000	0.169	0.034	0.000	0.177	0.036	0.000
C8	0.544	0.054	0.000	0.542	0.053	0.000	0.570	0.056	0.000
C9	-1.026	0.049	0.000	-0.942	0.048	0.000	-1.035	0.050	0.000
C10	-0.459	0.035	0.000	-0.382	0.034	0.000	-0.417	0.036	0.000
C11	0.267	0.037	0.000	0.307	0.036	0.000	0.344	0.038	0.000
C12	0.836	0.041	0.000	0.861	0.040	0.000	0.949	0.043	0.000
C13	0.633	0.039	0.000	0.623	0.039	0.000	0.682	0.041	0.000
C14	0.489	0.037	0.000	0.501	0.036	0.000	0.555	0.038	0.000
C15	0.920	0.031	0.000	0.907	0.031	0.000	0.995	0.032	0.000
C16	1.034	0.053	0.000	1.030	0.052	0.000	1.129	0.055	0.000
C17	-0.962	0.032	0.000	-0.936	0.033	0.000	-1.017	0.033	0.000
C18	-0.313	0.031	0.000	-0.285	0.030	0.000	-0.311	0.032	0.000
C19	0.212	0.036	0.000	0.201	0.036	0.000	0.219	0.038	0.000
C20	0.626	0.080	0.000	0.612	0.079	0.000	0.648	0.084	0.000
C21	-0.069	0.028	0.014	-0.009	0.028	0.755	-0.009	0.030	0.753
YEAR	-0.073	0.005	0.000	-0.072	0.007	0.000	-0.077	0.016	0.000
ρ				0.0405	.	.			
σ^2_{Hosp}							0.766	0.042	.
σ^2_{Year}							0.031	0.007	

Table 3.6.1c Wald Test Statistics and (P-Value) Comparing Models fit to IQI-25 (Bilateral Cardiac Catheterization Rate)

	Cross Sectional Model			Time Trend Model		
	SLR	GEE	GLMMIX	SLR	GEE	GLMMIX
SLR		466.78 (0.000)	4037.6 (0.000)		457.86 (0.000)	4035.7 (0.000)
GEE	146.63 (0.000)		213.69 (0.000)	145.58 (0.000)		214.20 (0.000)
GLMMIX	158.45 (0.000)	309.24 (0.000)		155.51 (0.000)	308.95 (0.000)	

* Wald Test uses the estimated covariance matrix from the model listed in each row

3.6.2 Provider-Level Model Predictions

Table 3.6.2 below provides the mean and standard deviation of differences between model predictions (expected rates above the diagonal, and risk-adjusted rates below the diagonal) from a random sample of 50 providers within the NIS reference population for IQI 17. For example, the mean difference in expected rates between the GEE and GLMMIX approaches for the cross sectional model was -0.016 (relative to a national mean response rate of 0.076 from Table 3.1). This estimated difference is quite high relative to the national mean response rate, demonstrating that model choice could have a significant effect on provider-level estimates.

Mean differences (and standard deviations) attributable to model specification (simple logistic vs GEE vs GLMMIX) for the risk-adjusted rates appear to be higher than the expected rates.

Table 3.6.2 Estimated Differences (and Standard Deviation) in Provider-Level Model Predictions of Expected and Risk Adjusted Rates for IQI-25 (Bilateral Cardiac Catheterization Rate)

	Cross Sectional Model			Time Trend Model		
	SLR	GEE	GLMMIX	SLR	GEE	GLMMIX
SLR		-0.005 (0.003)	0.016 (0.006)		-0.005 (0.003)	0.016 (0.006)
GEE	0.008 (0.008)		0.021 (0.003)	0.008 (0.007)		0.021 (0.003)
GLMMIX	-0.036 (0.044)	-0.044 (0.049)		-0.036 (0.045)	-0.044 (0.051)	

* In each 3x3 table above, Expected Rate Differences (and Standard Deviations) are above the diagonal, and Adjusted Rate Differences (and Standard Deviations) are below the diagonal.

4 Conclusions

This Section will be written after receiving comment and input from the workgroup participants. Some general conclusions are as follows:

- The potential effects of positive correlation among patients within the same hospital caused significant differences in the vector of parameter estimates in 2 of the five QI's selected for this investigation.
- The simple adjustment for a linear trend over time resulted in a highly significant negative slope for all QI's investigated.
- For 4 of the 5 QI's investigated, a change in the modeling approach did not create a meaningful difference in the expected rates (relative to the National mean response).
 - However, in many cases, the differences in provider-level estimates of expected and risk-adjusted rates between the modeling approaches were significantly different than zero based on the random samples of 50 providers. This is suggestive of a subtle, yet statistically significant bias.
- In some cases, there were significant differences between the GEE and GLMMIX approaches. These differences need to be more carefully investigated – in order to make a more definitive recommendation on the appropriate methodology to recommend for adjusting the models.
- Additional work could be done to exploit the potential added benefit of the distribution of random effects (from the GLMMIX modeling approach) to allow providers to assess where they might be located within the National distribution of providers (rather than a simple comparison of whether they are above or below the National mean response).

5 Continuing Investigations

While the workgroup participants are reviewing this draft report, Battelle will continue work on this investigation in the following areas:

1. Create Wald-Statistics based on the GEE and GLMMIX robust variance covariance matrices
2. Provide a descriptive and graphical summary of the distribution of estimated random effects intercepts (and slopes) from the GLMMIX cross sectional and time-trend models.
3. Assess model fit – particularly for situations in which there are statistically significant differences between the GEE and GLMMIX approaches.
4. Provide more specifics on the use of the random effects to identify where a provider is located within the national distribution of providers.

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Risk Adjustment and Hierarchical Modeling Workgroup

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